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14. ABSTRACT
The goal of this contract was to develop and demonstrate a machine learning framework for probabilistic vehicle state and model parameter inference, aiding the sensor integration and processing for the autonomous control of UAVs. The core technology that this approach is based on is the Sigma-Point Kalman Filter (SPKF). The current industry standard and most widely used algorithm for estimation is the extended Kalman filter (EKF). The EKF combines the sensor measurements with predictions coming from a model of vehicle motion (either dynamic or kinematic), in order to generate an estimate of the current navigational state (position, velocity, and attitude). This study points out the inherent shortcomings in using the EKF and presents, as an alternative, a family of improved derivativeless nonlinear Kalman filters called sigma-point Kalman filters (SPKF). We demonstrated the improved state estimation performance of the SPKF by applying it to the problem of loosely coupled GPS/INS integration. A novel method to account for latency in the GPS updates was also developed. A UAV (rotor-craft) test platform was used to demonstrate the results. Performance metrics indicate an approximate 30% error reduction in both attitude and position estimates relative to the baseline

15. SUBJECT TERMS
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Final Report

Sigma-Point Kalman Filter Based Sensor Integration, Estimation and System Identification for Enhanced UAV Situational Awareness & Control
Contract No.: N0014-02-C-0248

PI: Professor Eric Wan (ericwan@cse.ogi.edu), OGI

This report summarizes the major findings of the above mentioned research project as it stands at the close of the option year.

The goal of the base period effort has been to develop and demonstrate a machine learning framework for probabilistic vehicle state and model parameter inference, aiding the sensor integration and processing for the autonomous control of UAVs. The core technology that this approach is based on is the *Sigma-Point Kalman Filter* (SPKF). The successful results for this period were detailed at the 2003 ONR FNC Autonomy Review conference, previous progress reports, and also published in a number of publications [1,2,3]. The attached appendix summaries some of the more significant results and milestones achieved. The published papers may also be downloaded at: http://www.cse.ogi.edu/~ericwan/.

Although most of the base period development and experiments were performed using a high-fidelity software based simulation environment, we also successfully transitioned the SPKF code to a pseudo "real world" Matlab implementation that successfully runs on 'real' recorded flight telemetry in an offline fashion. Although ground truth reference state information is not available for "real flight" experiments, we did find a small but significant qualitative state estimation performance improvement between the baseline EKF used on board our UAV platform and our proposed SPKF implementation. Unfortunately, due to the unforeseen unavailability of our flight hardware (UAV) platform[1] we were unable to perform and exhaustive set of flight experiments either for the purpose of data collection or direct in-flight estimation performance comparison. See the attached appendix for a more detailed exposition of some of our real-flight data experimental results.

During the option year we set out to determine the effectiveness of leveraging the enhanced estimation performance of the SPKF framework (as determined in simulation during the base period), in order to achieve enhanced estimation performance in a GPS/INS system driven by a lower cost IMU. We aimed to compare the performance of our base (reference) system driven by a high cost ISIS IMU [4], with that of a system driven by a lower cost Crista IMU [5]. Our hypothesis was that the SPKF would be able to extract more useful information out of the lower quality Crista IMU signals, which has

[1] *UAV Platform Issues*: We used the DARPA SEC supported helicopter platform (UAV) for data acquisition and flight experiments. However, one week prior to the end of the contract, we were informed that all government purchased equipment was to be delivered to AFRL/DARPA (by end of February, 2004).

higher levels of bias, drift and noise) than would be possible with a similar EKF implementation. Unfortunately, due to the premature unavailability of our UAV flight hardware, we were never able to fly both the ISIS and Crista IMUs in parallel for flight data collection. This forced us to revert to less than ideal "ground based" parallel IMU data collection. For this purpose we placed the UAV avionics box (flight computer and sensors) inside a motor vehicle and collected GPS, Altimeter and IMU (ISIS and Crista) data while driving around pre-determined routes. These datasets were then used as input to our SPKF and EKF based navigation filters in order to estimate the true underlying states (position, velocity and attitude) of the vehicle. See the appendix for a summary of the results. Contrary to our results on the helicopter (UAV) estimation experiments, the ISIS/Crista comparison experiments on *ground vehicle* data did not show significant difference between the EKF and SPKF approaches. Although the higher quality (lower noise, bias and drift) ISIS IMU data allows for more accurate estimates than the Crista data, the differences are quite subtle. This is most probably due to the limited dynamic range of the maneuvers performed by the ground vehicle during data collection, compared to that of the UAV. The nonlinear effects of the vehicle dynamics (with respect to the time scale / sampling rate of the IMU) play a bigger role in estimator accuracy when the vehicle maneuvers are more aggressive.

In conclusion, we maintain that the SPKF provides a superior integration filter than the EKF. However, expected gains are problem specific, and remain difficult to predict. The advantages of the SPKF cannot completely compensate for poor quality sensor components. While we have focused on IMU/GPS integration, the use of the SPKF is applicable to the broad field of inference and sensor fusion, with expected gains over traditional EKF filtering.

References

[1] R. van der Merwe, "Sigma-Point Kalman Filters for Probabilistic Inference in Dynamic State-Space Models," Ph.D Thesis, OGI School of Science & Engineering, Oregon Health & Science University. April 2004.

[2] R. van der Merwe and E. Wan, "Sigma-Point Kalman Filters for Integrated Navigation," in *Proceedings of the 60th Annual Meeting of The Institute of Navigation (ION),* (Dayton, Ohio), June 2004.

[3] R. van der Merwe, E. Wan, S. Julier, A. Bogdanov, G. Harvey, and J. Hunt "Sigma-Point Kalman Filters for Nonlinear Estimation and Sensor Fusion: Applications to Integrated Navigation," in *Proceedings of the AIAA Guidance Navigation & Control Conference,* (Providence, RI), August 2004.

[4] *Inertial Science, Inc.* ISIS-IMU. http://www.inertialscience.com/isis_imu-new.htm

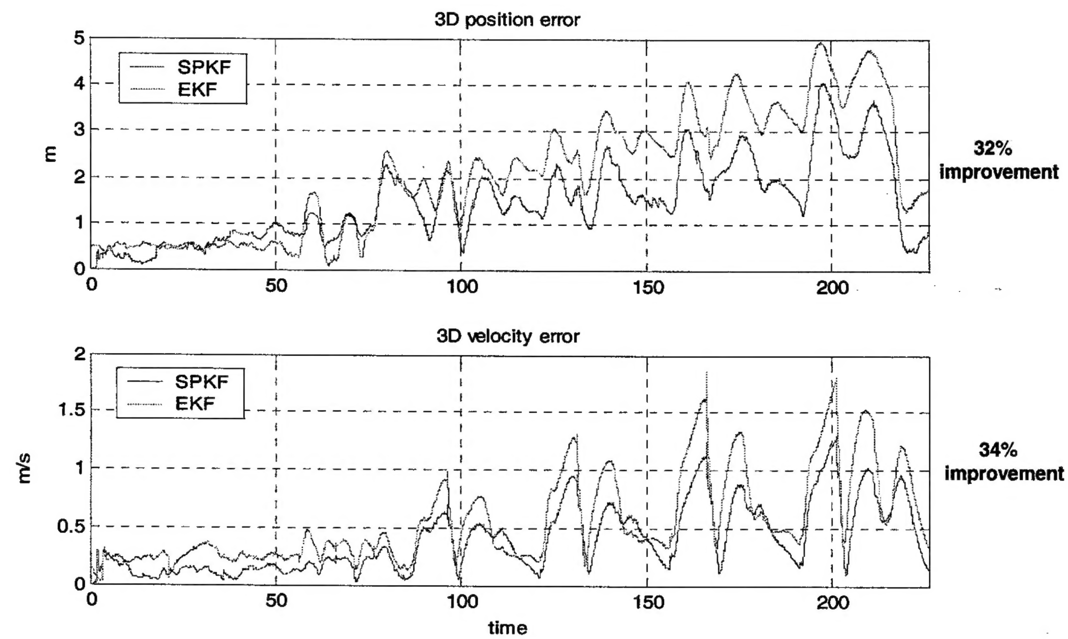
[5] *Cloud Cap Technology,* Crista-IMU. http://www.cloudcaptech.com/crista_imu.htm

Appendix: Summary of significant results

State Estimation

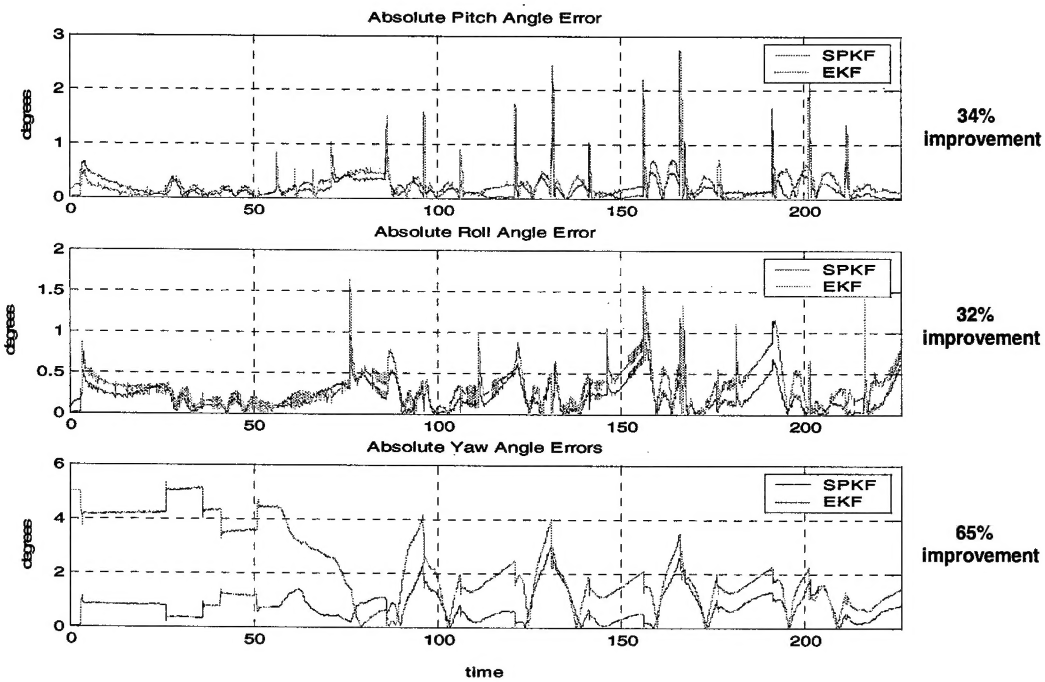
After a thorough literature review, we decided to implement our SPKF based state-estimator using the same kinematic-model approach as used in other state-of-the-art strapdown Kalman filter augmented IMU/GPS navigation systems. This allows for a robust generic estimation system that can be implemented in real-time and which can easily be adapted (transferred) to a variety of UAVs. Furthermore, using a SPKF within the state-estimator allows for an elegant solution to the GPS sensor-latency problem that plagues EKF based solutions. The state estimation error improvement of our SPKF based system over that of a state-of-the-art EKF based solution is shown in the plots below.

This plot shows the magnitude of the 3D position and velocity estimation errors for both the EKF and SPKF as measured against the ground-truth state of the UAV during a series of aggressive maneuvers which were performed in simulation. Our system reduces the error by about 33%.



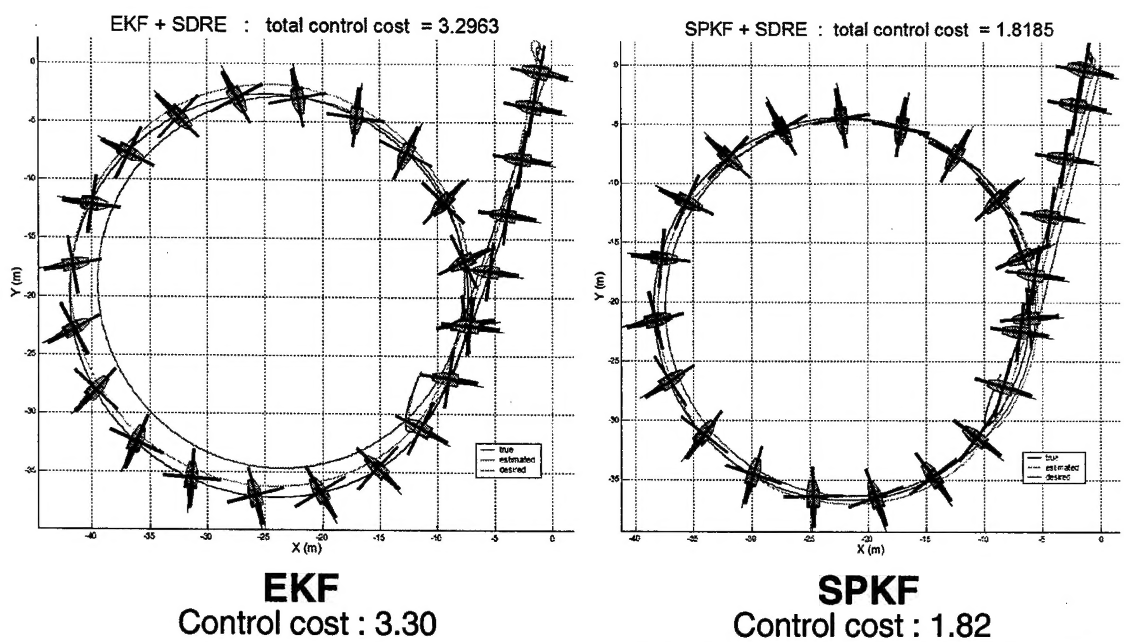
This plot shows the magnitude of the 3D attitude errors (pitch, roll and yaw angles) for both the EKF and SPKF as measured against the ground-truth state of the UAV during a series of aggressive maneuvers which were performed in simulation. Our system reduces

the error by about 33% for the pitch and roll whereas the yaw error is improved by 65%. Note also the reduced high frequency errors and "spikes" (as apparent in the EKF) where aggressive motion results in more nonlinear dynamics.

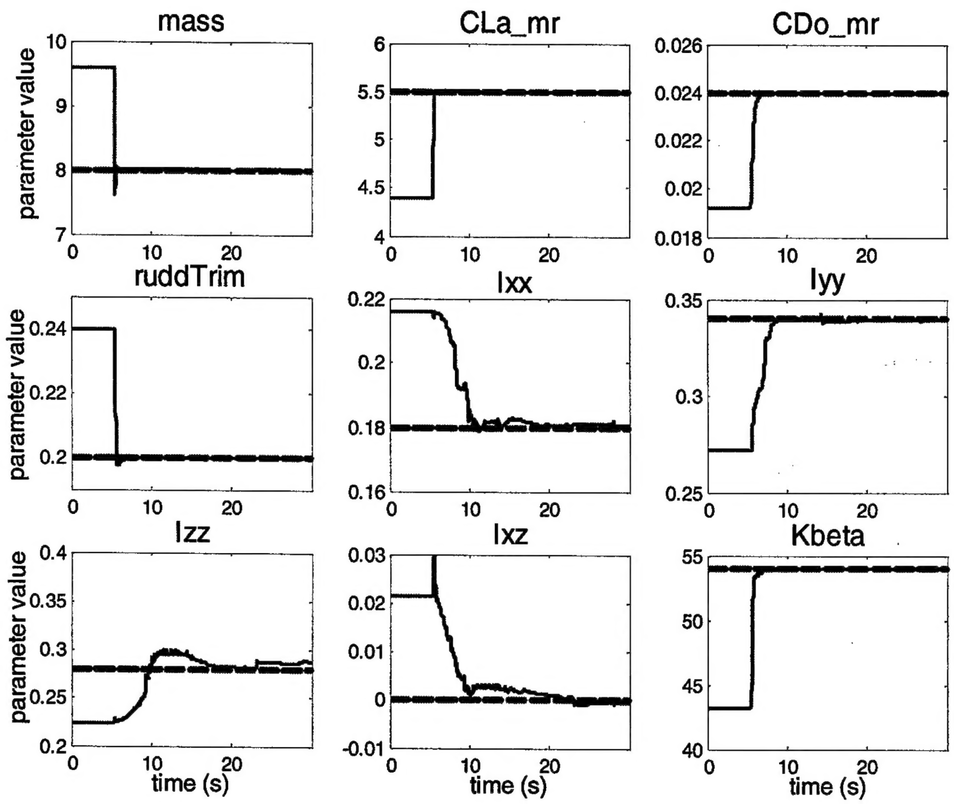


Control Cost

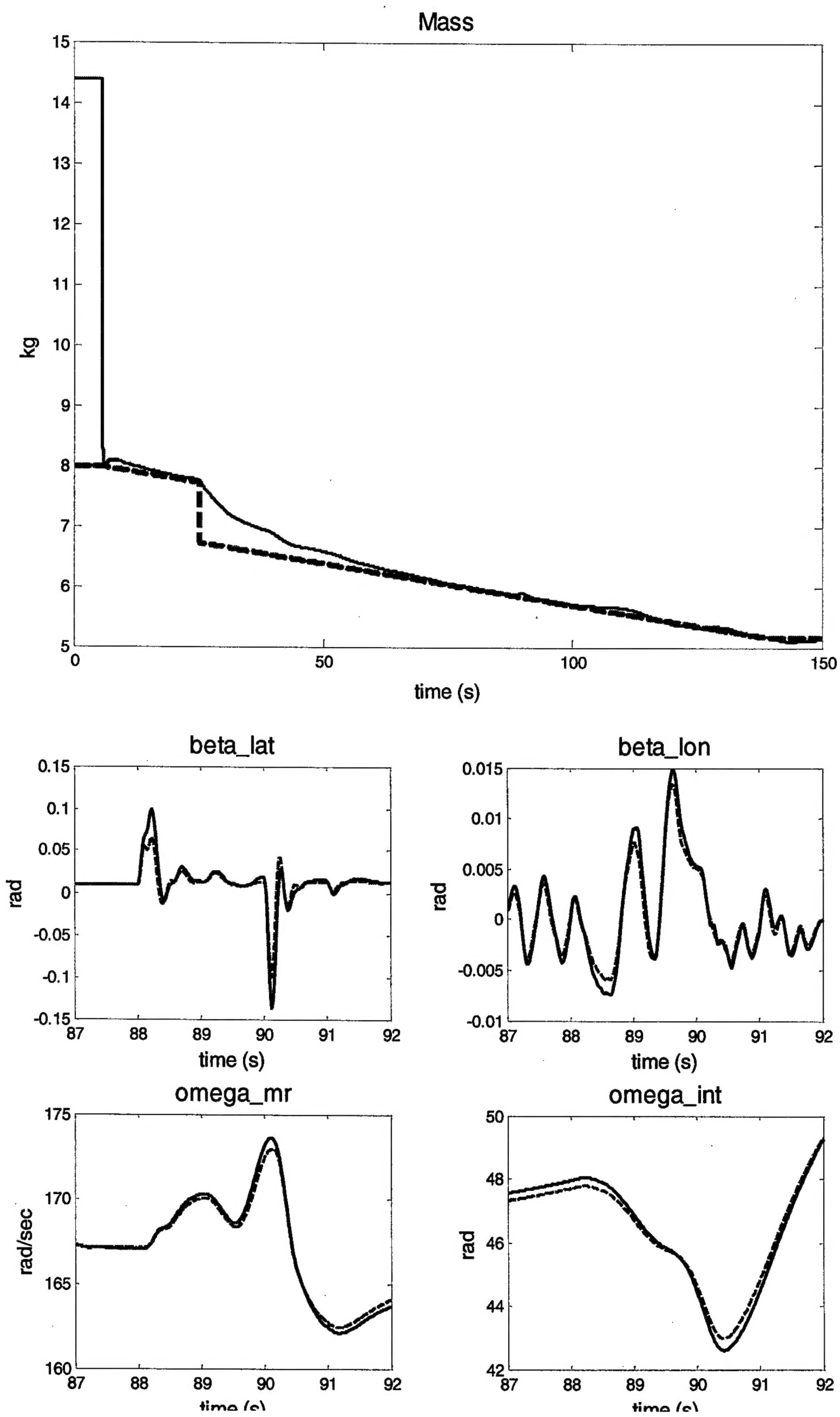
- **Use of SPKF estimator reduces control cost by 45%**



We also successfully implemented a SPKF based parameter estimator as well as a SPKF based joint state and parameter estimator. The parameter estimator uses the true states for validation purposes. The joint filter uses the accurate navigational state solution of the kinematic-model-based SPKF to estimate the remaining hidden states of the vehicle dynamics as well as track certain model parameters. This also requires use of the full high-fidelity model of the vehicle dynamics. The plots below show some of our simulation results. The first plot shows how a SPKF based parameter estimator accurately converges to the true value of some of the system parameters (masses, moments of inertia, etc). The true values are shown in red and the estimated values in blue.

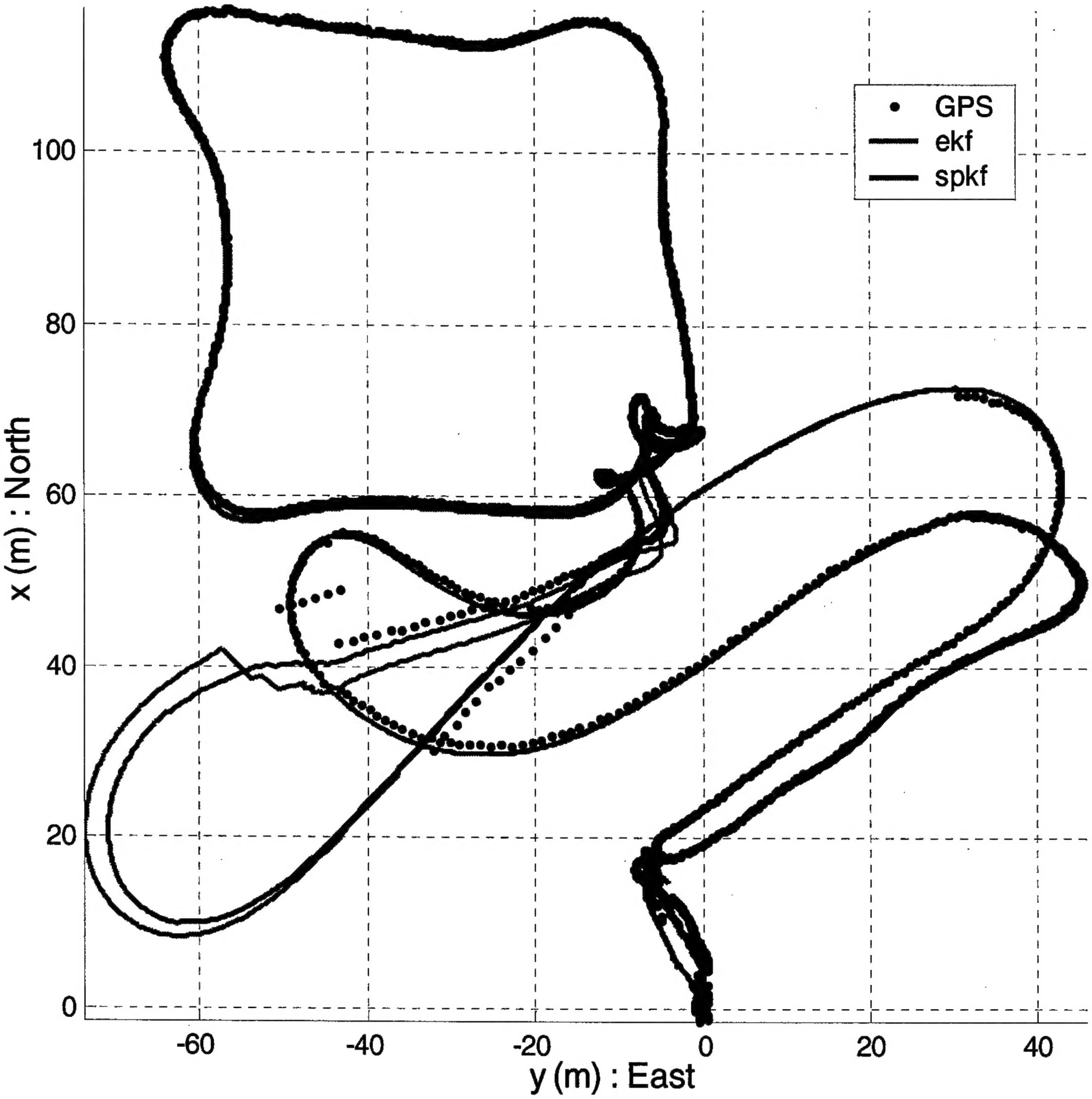


The next plot shows some of our preliminary results using the full joint-estimator. We track the mass and certain hidden states (flapping angles, rottor speed, etc.) of the UAV over time as we simulate a time-varying payload weight. This reflects the real-world effect of fuel consumption and payload delivery (at t=25).

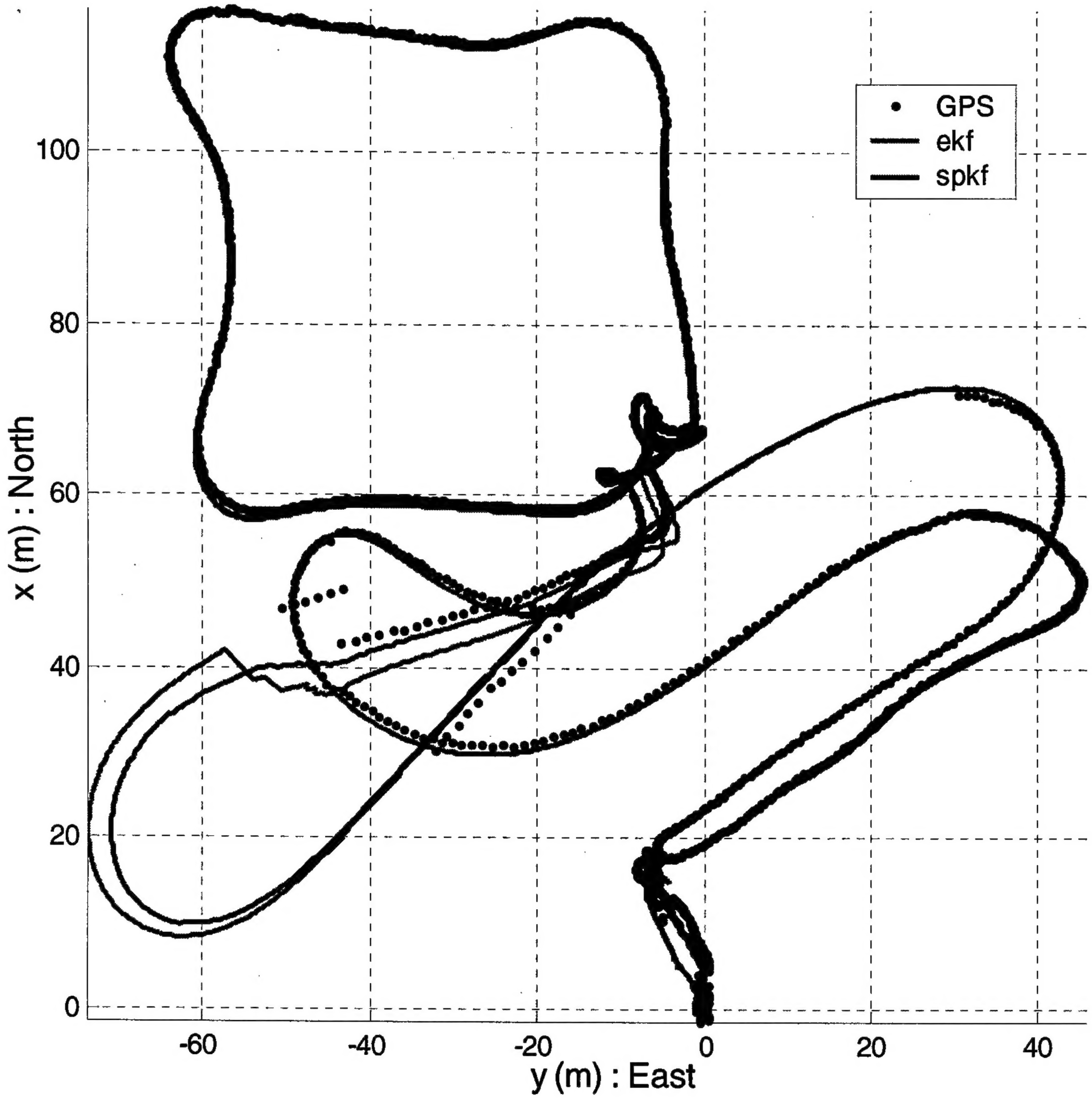


Results on Real Flight Data

SPKF Based GPS/INS System: We successful implemented a high quality SPKF based state estimator which can operate on real flight-data in an offline manner. Both GPS latency compensated and non-compensated versions of the estimator is implemented. This implementation was done using optimized Matlab code. In order to use this code for real-time (in flight) estimation, the Matlab code will need to be ported to a lower level system language such as C or C++.

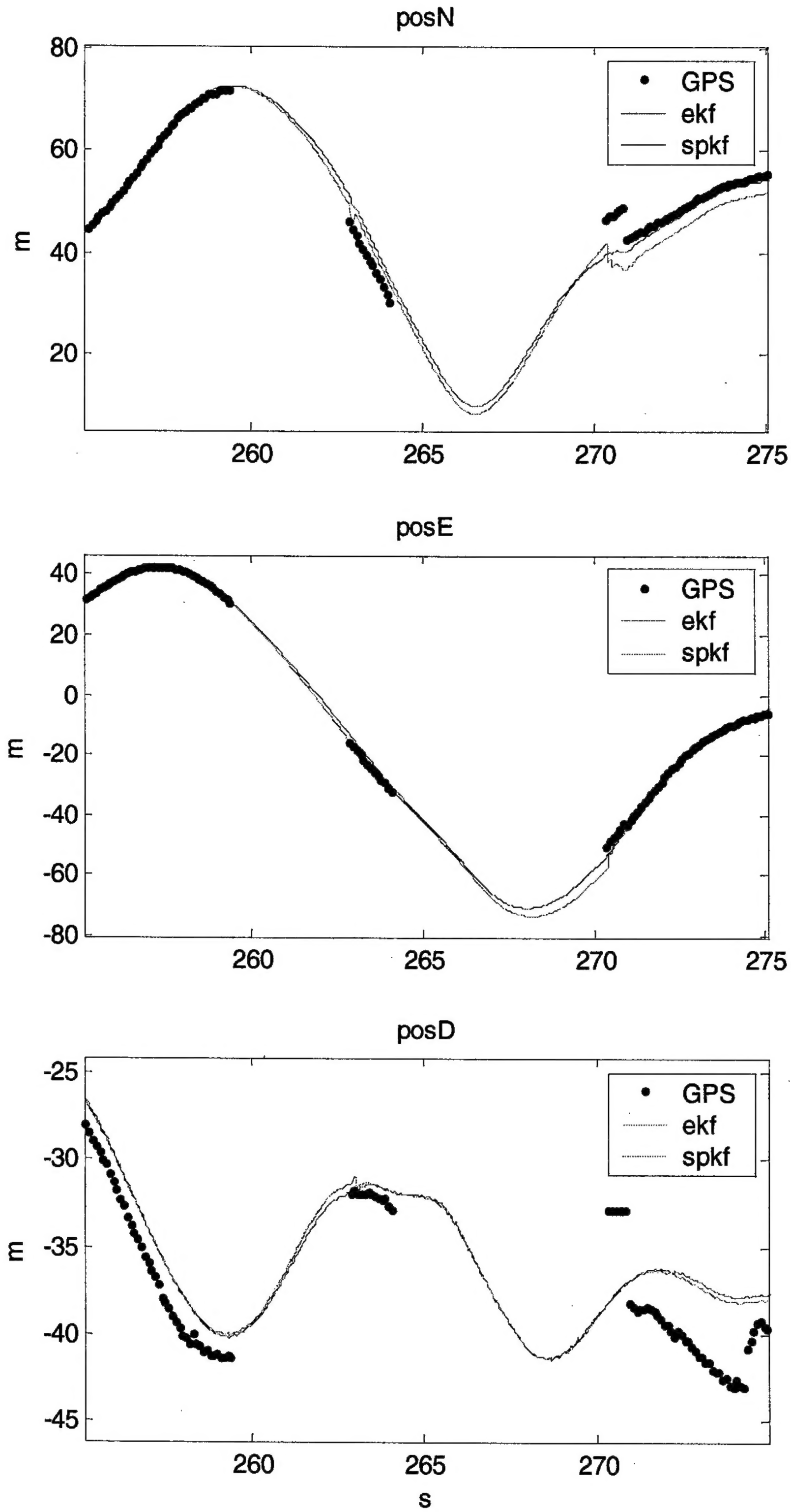


The figure above shows the estimation results of our SPKF based estimator compared to that of the built in MIT-designed EKF based system on real flight telemetry. The UAV was flown under pilot guidance to altitude. At this point the system was switched over to fully autonomous flight. The flight plan was as follows: First the UAV held steady in hover for a number of seconds, after which it flew a square trajectory at a constant altitude of about 55-60 meters. Since no 'ground truth' signal is available for absolute error comparison, we need to evaluate the results on more subjective terms. For this purpose, a top-down (2D) projection of the above results is quite insightful (see next figure):



Notice the significant number of GPS outages that occurred during the pilot guided ascent to the hovering altitude (s-shaped curve). Clearly the SPKF seems to more accurately track the (assumed) true underlying trajectory during this outage period than the EKF. The EKF generated position estimate exhibits an erratic jump just before the GPS measurements becomes available again (see plot above at coordinates x=40,y=-60). This is probably due to the inherent nature of the INS solution (derived from integrating the bias compensated IMU gyro and accelerometer data) to drift during periods of GPS outage (no Kalman filter measurement update). Since the SPKF performs a more accurate time-update during these periods than the EKF, and possibly also more accurately track the underlying IMU biases, the resulting SPKF estimates seems to be more robust to GPS outages in general. We are still investigating these claims further for robustness, etc.

The plot on the next page shows the effect of this on the separate north, east and down components of the estimated 3D position: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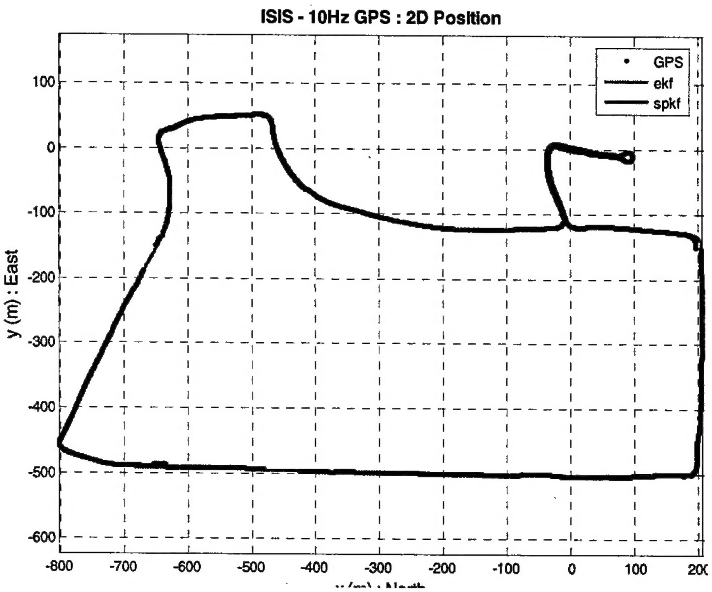
ISIS - 10Hz GPS : 2D Position
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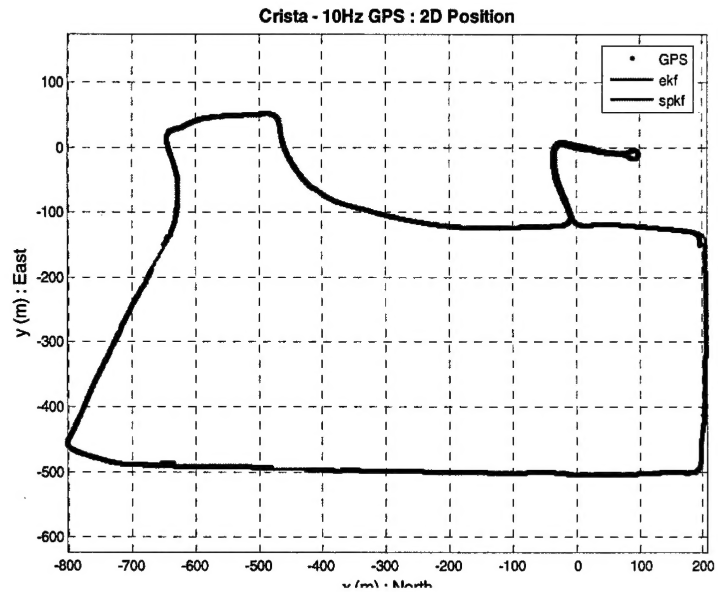
y (m) : East


Crista - 10Hz GPS : 2D Position
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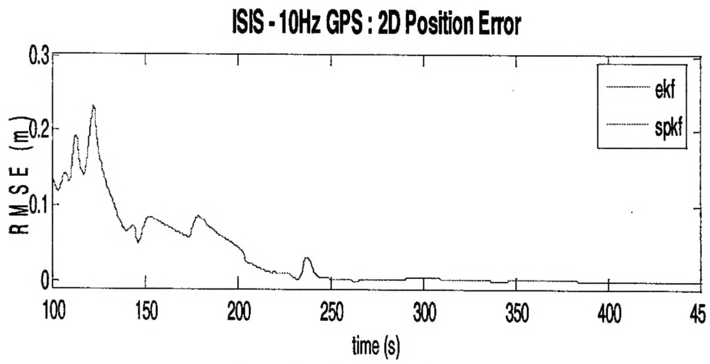
y (m) : East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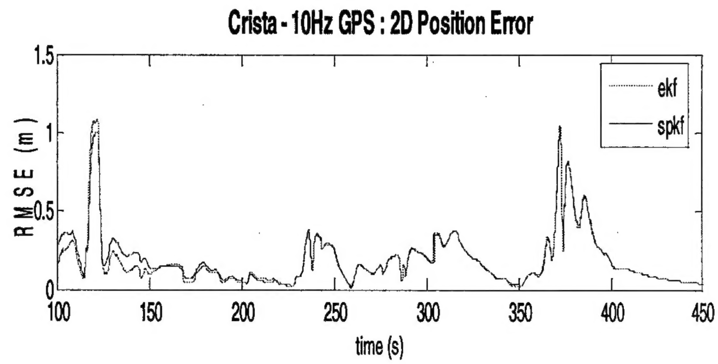
R M S E (m)
time (s)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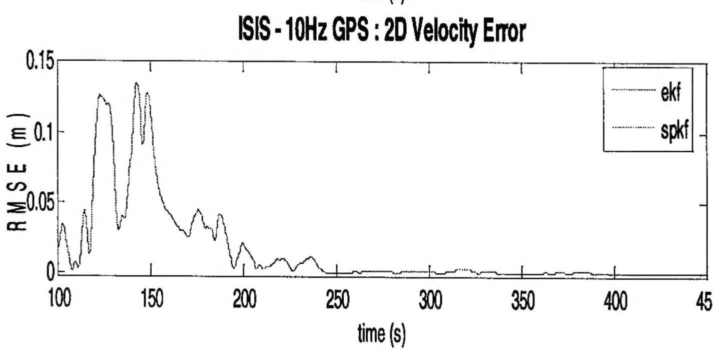
spkf
R M S E (m)
time (s)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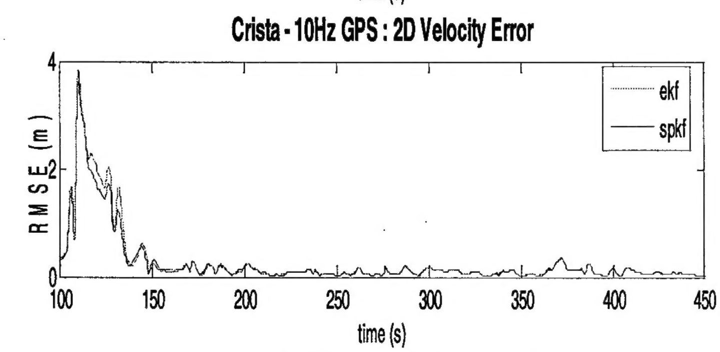
R M S E (m)
time (s)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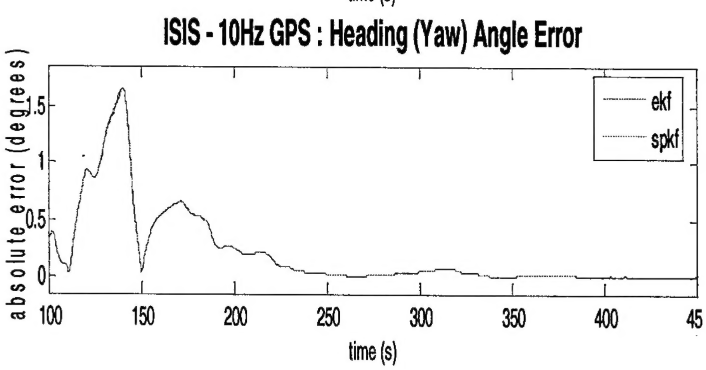
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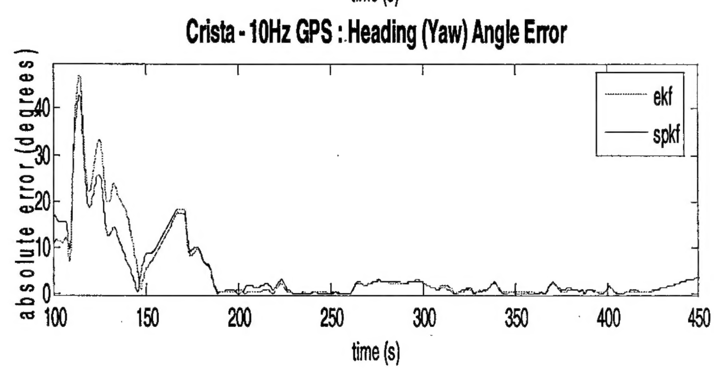
absolute error (degrees)
time (s)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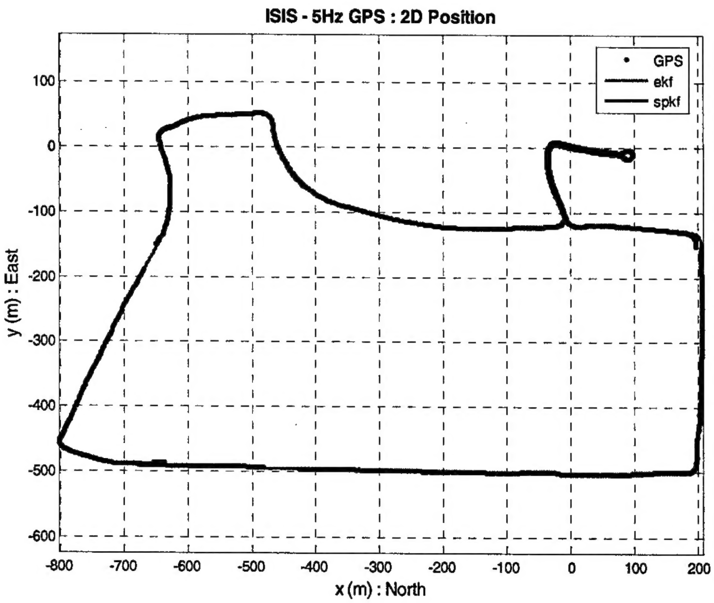
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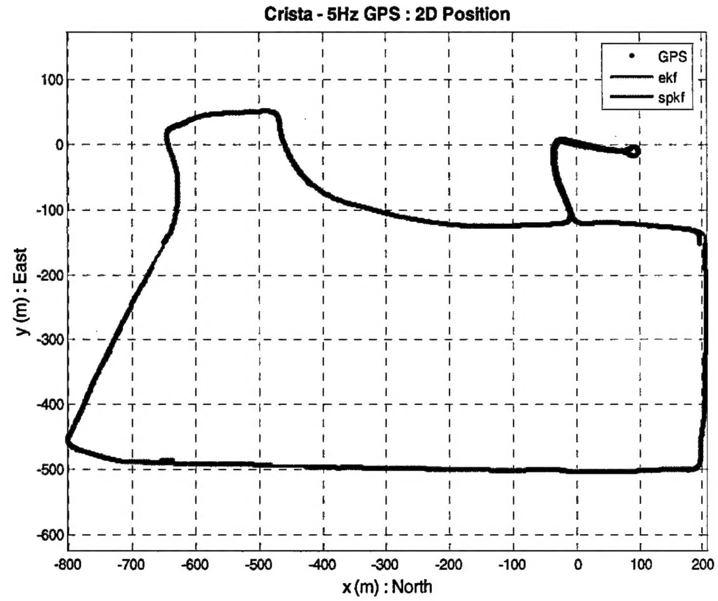
x (m) : North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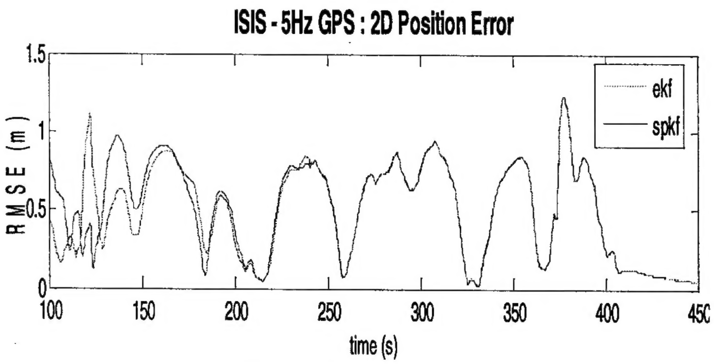
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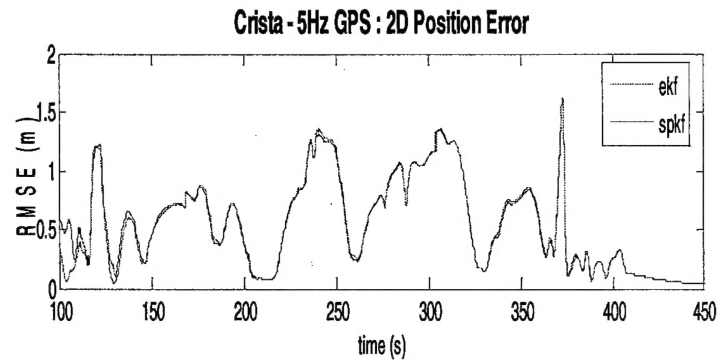
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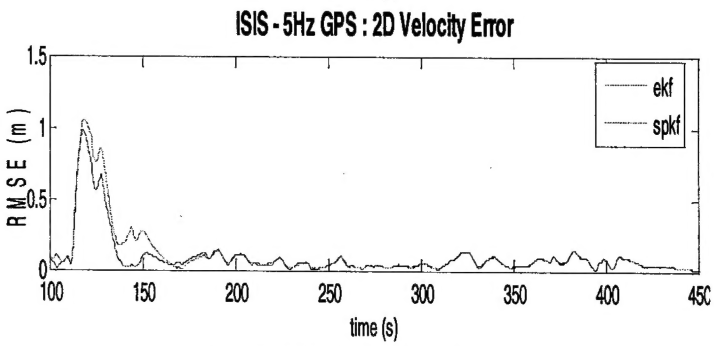
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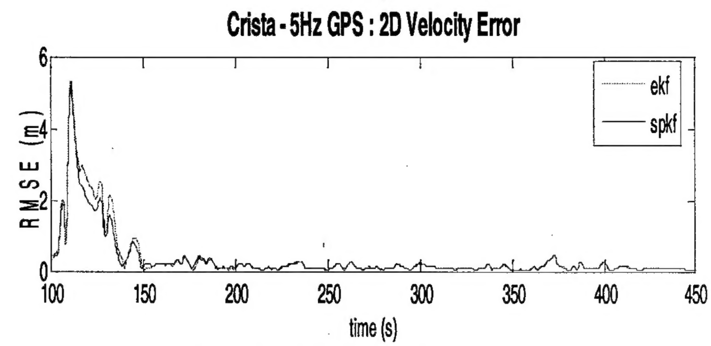
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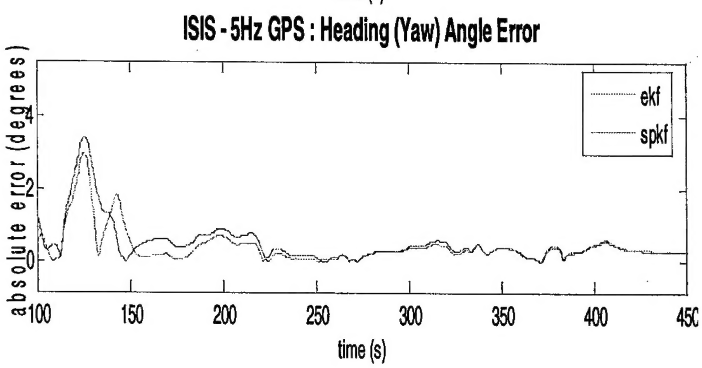
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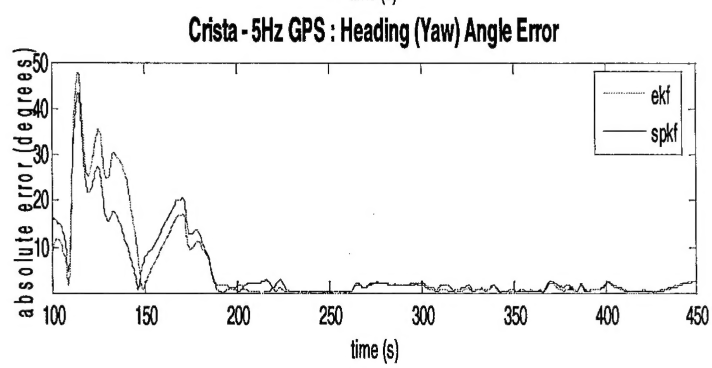
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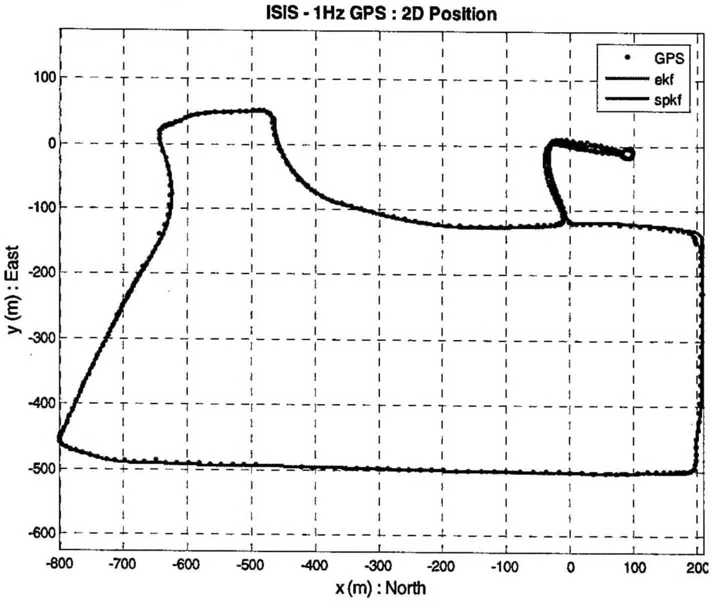
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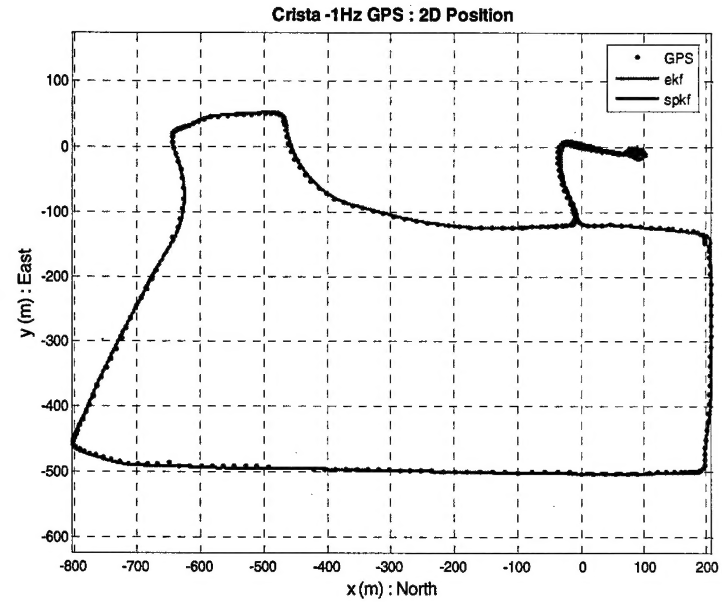
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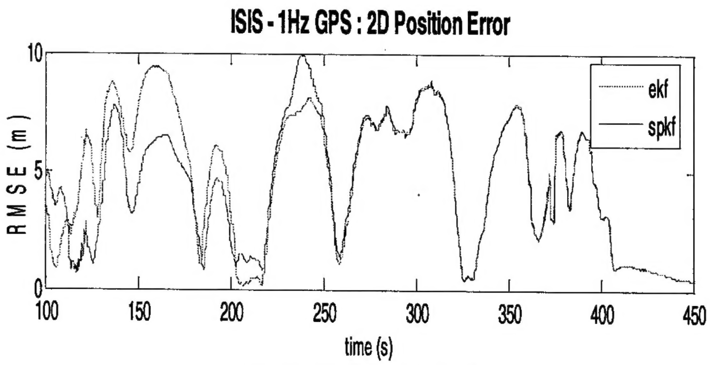
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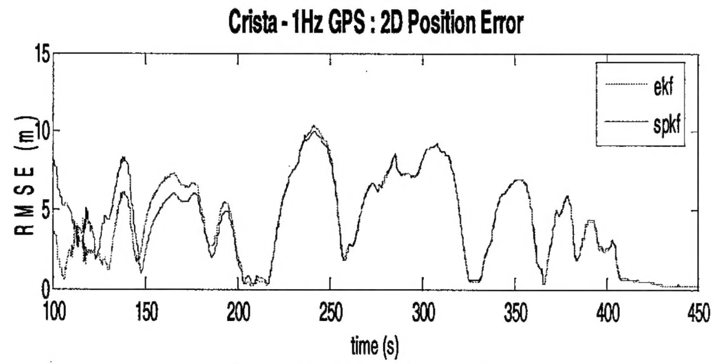
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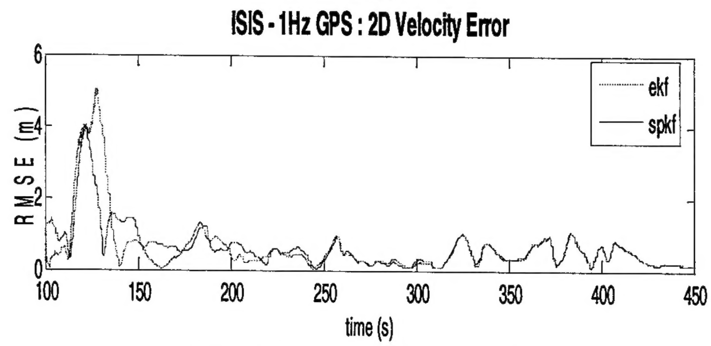
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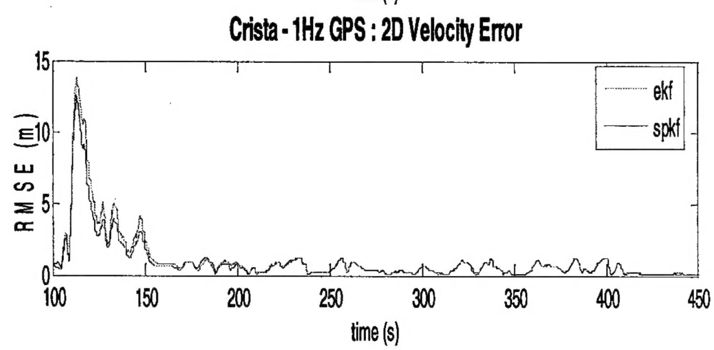
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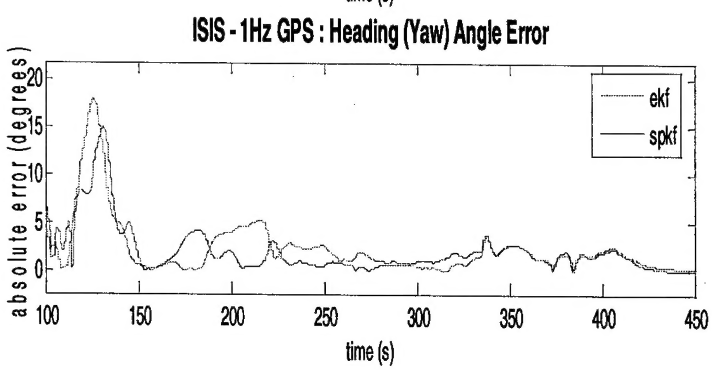
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absolute error (degrees)
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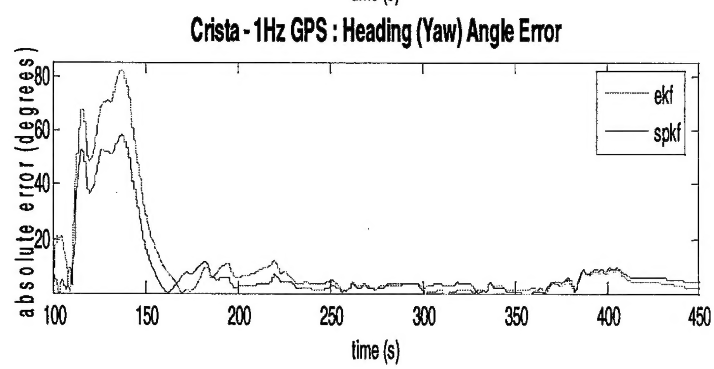
Crista - 1Hz GPS : Heading (Yaw) Angle Error
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absolute error (degrees)
time (s)

Software

We released a toolkit containing all of the base estimation algorithms (SPKF variants) as well as a general implementation framework for probabilistic inference and machine learning within a dynamic state-space models. The toolkit, ***ReBEL***, forms part of the deliverables for this project. For more download information, see: http://choosh.bme.ogi.edu/rebel.

Specific UAV centric SPKF (SR-CDKF) implementations of the navigation filter is also included as part of the deliverables, and is provided separately. These Matlab code routines are well commented/documented and should allow for easy leveraging to ONR specific platforms.